# Non-Local Super-resolution of Missing Data in Multi-sensor Observations of Sea Surface Geophysical Fields

Ronan Fablet, François Rousseau

# NON-LOCAL SUPER-RESOLUTION OF MISSING DATA IN MULTI-SENSOR OBSERVATIONS OF SEA SURFACE GEOPHYSICAL FIELDS

*R. Fablet, F. Rousseau*

Institut Mines-Télécom/Télécom Bretagne; UMR 6285 LabSTICC
Technopôle Brest Iroise, Brest, France
{ronan.fablet,francois.rousseau}@telecom-bretagne.eu,perso.telecom-bretagne.eu/ronanfablet

## 1. PROBLEM STATEMENT AND RELATED WORK

The ocean surface is monitored with a dense network of satellites. Various satellites record images of multiple ocean parameters at different resolutions. As a peculiar example, Sea surface temperature (SST), which is the temperature of the thin ocean's upper layer, is a peculiar example. Microwave (MW) radiometry provides low resolution observation (0.5°-0.25°, 25/50km) while infrared (IR) sensor delivers high resolution SST measurements (up to 0.02°, 1km). SST Monitoring is of high interest as SST observations are key observations for a wide range of studies, including weather forecasting, ocean circulation, global warming impacts.

Beyond their intrinsic resolution, the different satellite sensors also differ in their sensitivity to the atmospheric conditions, and especially the cloud coverage. Whereas microwave radiometers involve very low missing data rates, IR sensor may result in high missing data rates (up to 90% over several consecutive days in some regions). Operational level-4 products provide interpolated fields, which typically rely on covariance-driven krieging-based approaches (e.g., [3]). The joint exploitation of the multi-source multi-scale data remains however a challenge to produce geophysically consistent interpolated fields.

In this context, we address here the interpolation of missing data in high-resolution geophysical fields under the assumption that a simultaneous low-resolution observation is available. Such multi-scale interpolation is expected to depict geophysically consistent features, especially: i) consistent high-resolution textured patterns, ii) non-Gaussian marginals and iii) specific spectral density. We propose a novel model to address this multi-scale interpolation jointly accounting for the above-mentioned constrains. The key idea is to exploit a non-local or patch-based framework [2, 5]. Such exemplar-based representation provides an implicit texture model, which directly exploits available observations to reconstruct consistent geophysical patterns.

## 2. EXEMPLAR-BASED INPAINTING AND NON-LOCAL REGULARISATION

Among the recent advances in texture modelling and texture-based super-resolution, patch-based techniques are particularly appealing to reconstruct and simulate textured images from previous observations [1, 2, 5]. In this context, non-local regularisation priors introduce an energy minimisation and inverse image problems are stated as the minimisation of a global energy:

$$\widehat{I} = \arg\min_{I} U_{obs}\left(I, I_{obs}\right) + \gamma U_{NLReg}\left(I\right) \tag{1}$$

In the simplest cases, observation term $U_{obs}\left(I, I_{obs}\right)$ resorts to a quadratic error term $\|I - I_{obs}\|^2$. Non-local prior $U_{NLReg}\left(I\right)$ involves the reconstruction of image $I$ from a reference patch database, where a patch is a $N \times N$ local window of an image with N typically ranging from 3 to 15. Let us denote by $\{\mathcal{A}_k\}_{k\in\mathcal{K}}$ the colected set of representative image patches, and $p_0$ the pixel referring to the center of the patch. Following [5], non-local prior $U_{NLReg}(I)$ is stated as:

$$U_{NLReg}(I) = \|I - \mathcal{P}_{NLM}(I, \{\mathcal{A}_k\})\|^2 \tag{2}$$

where $\mathcal{P}_{NLM}(I, \{\mathcal{A}_k\})$ is the non-local projection of image $I$ onto patch database $\{\mathcal{A}_k\}$ given by a non-local mean [5]

$$\forall p, \;\; \mathcal{P}_{NLM}(I, \{\mathcal{A}_k\})(p) = \sum_{k \in \mathcal{K}} w_k(I, \mathcal{A}_k, p)\mathcal{A}_k(p_0) \tag{3}$$

and $w_k(I, \mathcal{A}_k, p)$ is the normalised weight stating the contribution of patch $\mathcal{A}_k$ to the projection of image $I$ at pixel $p$. It is computed as : $w_k(I, \mathcal{A}_k, p) \propto \exp[-\eta \cdot d(I, \mathcal{A}_k, p)\ ]$ with $d(I, \mathcal{A}_k, p)$ the mean square difference between reference patch $\mathcal{A}_k$ and the patch of size $N \times N$ around $p$ in image $I$. $\nu$ is a model parameter. Among the different applications of non-local regularization techniques in inverse image problems, one may cite for instance denoising, segmentation, super-resolution, inpainting issues....

## 3. NON-LOCAL SUPER-RESOLUTION OF MISSING DATA

Here, we investigate non-local models for the super-resolution of missing data in high-resolution observation of the sea surface with two basic constraints:

- the low-resolution projection of the reconstructed image $I$, denoted as $\mathcal{P}_{LR}[I]$ should conform to the observed low-resolution image $I_{LR}^{obs}$. For the reported numerical experiments, we exploit a wavelet-based low-resolution projection;
- the reconstructed image $I$ should conform to the high-resolution image $I_{HR}^{obs}$ for the actually observed image domain $\Omega$;

Besides, as stressed above, geophysical fields typically involve specific non-Gaussian marginal distributions and power spectral densities. We then consider two additional constraints:

- the reconstructed image $I$ should depict a reference radial power spectral density $PSF^*$
- the high-resolution detail $I - \mathcal{P}_{LR}[I]$ should conform to an expected non-Gaussian marginal distribution.

Both reference radial power spectral density $PSF^*$ and $\mathcal{D}_\theta$ might be set a priori or inferred from the observed data using both parametric and/or non-parametric models. In the reported experiments, we consider here parametric models, namely power laws for the radial power spectral density and a generalized Gaussian model for the marginal distribution of the details. Both models were shown to relevantly fit to the observed data. Other parametric models and non-parametric models may be considered without any loss of generality. Formally, we resort a non-local framework and state the super-resolution of missing data as a constrained minimization issue as follows:

$$I_{HR} = \arg\min_I \|I - \mathcal{P}_{NLM}(I, \{\mathcal{A}_k\})\|^2 \quad \text{Subject to} \begin{cases} I_{HR}(\Omega) = I_{HR}^{obs}(\Omega) \\ \\ \mathcal{P}_{LR}[I] = I_{LR}^{obs} \\ \\ I(p) - I_{LR}(p) \propto \mathcal{GG}_{\sigma,\alpha} \\ \\ rPSF(I)(\omega) = \beta\|\omega\|^\nu \end{cases} \tag{4}$$

where $\mathcal{P}_{nlm}(I)$ refers to the non-local projection of image $I$ given by (Eq.3), $\mathcal{GG}_{\sigma,\alpha}$ the centered generalised Gaussian distribution fitted to the marginal distribution of the observed high-resolution detail with scale parameter $\sigma$ and exponent $\nu$.

Regarding the numerical resolution of the above constrained minimization, it might be noted that all terms and constraints can be regarded as projection onto an image subspace. Especially, the constraint on the marginal distribution of the high-resolution details can be solved for using a contrast change to fit the expected marginals, and the spectral constraint resorts to an isotropic filtering, performed in the Fourier domain.The proposed numerical scheme then iterates the following steps : i) non-local projection, ii) contrast change onto the the high-resolution details to fit the expected marginal distribution, iii) Fourier-based filtering to match the expected spectral law, iv) low-resolution and interpolation constraints. As initialization, we consider the projection of a null or white noise image onto the low-resolution and interpolation constraints. Our model involves two key parameters: the patch size $N \times N$ and scale parameter $\beta$ for the non-local projection $\mathcal{P}_{NLM}(\cdot, \{\mathcal{A}_k\})$. In the reported results, we use $N = 7$ and $\eta = 50$.

## 4. RESULTS

We report in Fig.1 an example of super-resolution of missing data using the proposed scheme. Given a high-resolution SST observation, we simulate an associated low-resolution observation using a 16-downsampling factor and a Daubechies-6 low-pass filter. It might be stressed that this downsampling rate is important and in the range of the downsampling factor between high-resolution infrared SST and low-resolution microwave SST. We randomly generate a missing data mask accounting for 20% of the image area. As patch database, we randomy select 5000 image patches from high-resolution image patches with no missing data. The reported example demonstrates that we reconstruct consistent high-resolution geophysical field which actually jointly account for four key features: a low-resolution component which conforms to the low-resolution observation, high-resolution information provided by the high-resolution data if available, the expected patterns of the radial power spectral density and of the marginal distribution of the high-resolution details. To our knowledge, existing state-of-the-art models cannot jointly fulfill these four constraints.

These results stress the relevance of patch-based and non-local approaches for super-resolution issues in remote sensing applications. Our ongoing work addresses the exploitation of the proposed model as a sampling prior within an ensemble Kalman scheme to produce temporally and spatially consistent time series of SST fields from multi-sensor observation.


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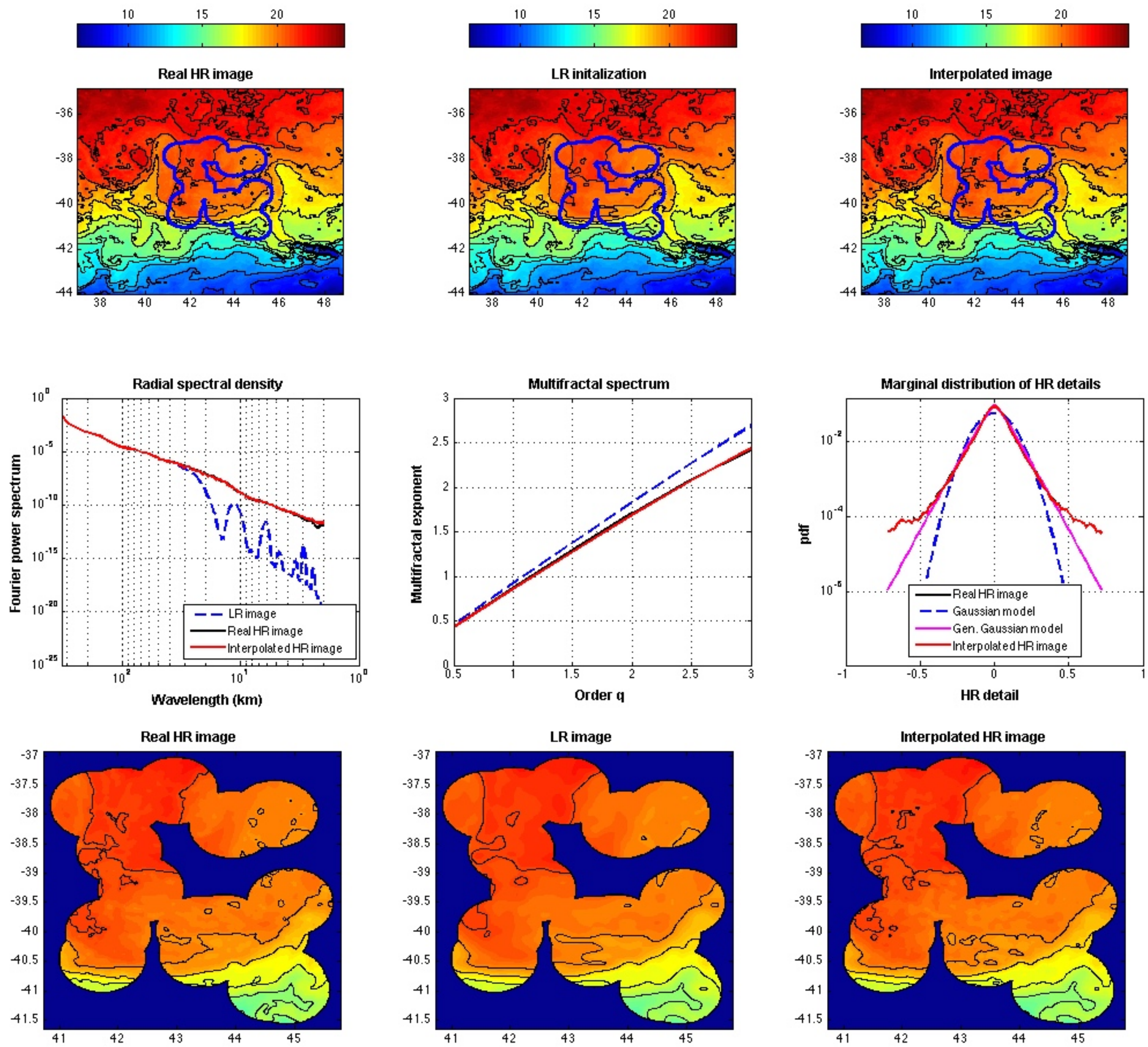


**Fig. 1**. Ilustration of the proposed super-resolution of missing data in a high-resolution observation given the associated low-resolution observation: first row, real high-resolution (HR) image, initial interpolation using the low-resolution image, interpolated image using the proposed non-local model; second row, radial spectral densities of the real HR image (black,-), the real LR image (blue, –) and the interpolated image (red,-), multifractal spectrum, marginal distribution of the HR details, third row, zoom on the missing data area for the real HR image, the real LR image and the interpolated image.